

A Review: Removal of Impulse Noise in Image

Vijimol V V¹, Anilkumar A.²

¹(Department of computer science ,College of Engineering Karunagapally,India)

²(Department of computer science ,College of Engineering Karunagapally,India)

ABSTRACT: Images are often corrupted by impulse noise in the procedures of image acquisition and transmission. In this paper, there is a study on denoising scheme and its architecture for the removal of random valued impulse noise. To achieve the goal of low cost, a low-complexity architecture is proposed. Decision-tree-based impulse noise detector to detect the noisy pixels, and an edge-preserving filter to reconstruct the intensity values of noisy pixels. Furthermore, an adaptive technology is used to enhance the effects of removal of impulse noise. Extensive experimental results demonstrate that the proposed technique can obtain better performances in terms of both quantitative evaluation and visual quality than the previous lower complexity methods. Moreover, the performance can be comparable to the higher complexity methods.

Keywords: DTBDM(Decision Tree Based Impulse Detector Method), Noise Removal, Edge Oriented Noise filter.

I. INTRODUCTION

Image processing is widely used in many fields, such as medical imaging, scanning techniques, printing skills, license plate recognition, face recognition, and so on. In general, images are often corrupted by impulse noise in the procedures of image acquisition and transmission. The noise may seriously affect the performance of image processing techniques. Impulsive noise always significantly damages an image. Noise with even a small corruption rate can corrupt most important details. Images are often corrupted by impulse noise due to errors generated in noisy sensors or communication channels. It is important to eliminate noise in the images before some subsequent processing, such as edge detection, image segmentation and object recognition. The corruption by impulse noise is a frequently encountered problem in image acquisition and transmission. Attenuation of noise and preservation of details are usually two contradictory aspects of image processing. Impulsive noise filtering is an important field in image processing. Also digital images are often corrupted by impulse noise due to transmission errors, malfunctioning pixel elements in the camera sensors, faulty memory locations, and timing errors. The intensity of impulse noise has the tendency of being either relatively high or relatively low. Thus, it could severely degrade the image quality and cause some loss of information details.

II. NOISE DETECTION TECHNIQUES

2.1 Impulse noise detection

Images are often corrupted by impulse noise due to errors generated in noisy sensors or communication channels. So far, many techniques have been proposed to remove impulse noise from the corrupted images. A good solution to this problem is noise detection implemented prior to filtering. If the corrupted pixels are identified and they are a priori known before filtering, then the filter can be applied only to these pixels. There have been much more methods for removing the impulse noise and some of them are explained in following sections. Pei-Yin[1] proposed a new impulse detector. The cost of implementation depends mainly on the required memory and computational complexity. Hence, less memory and few operations are necessary for a low-cost denoising implementation. Based on these two factors, he proposed a simple edge-preserved denoising technique (SEPD) and its implementation for removing fixed-value impulse noise. The storage space needed for SEPD is two line buffers rather than a full frame buffer. Only simple arithmetic operations, such as addition and subtraction, are used in SEPD.

[1] proposes a useful impulse noise detector to detect the noisy pixel and employ an effective design to locate the edge of it. The experimental results demonstrate that SEPD can obtain better performances in terms of both quantitative evaluation and visual quality than other state-of-the-art lower-complexity impulse denoising methods. Furthermore, the implementation of [37] method also outperforms previous hardware circuits in terms of quantitative evaluation, visual quality, and hardware cost. In [2], Igor Aizenberg proposes a new solution for impulse detection, an impulse detector that can be used with different nonlinear filters for effective detection of

impulses in images containing impulsive noise. We will call it a differential rank impulse detector (DRID). This detector is based on two estimations. The first estimation is a comparison between the rank (the position in variational series) of the pixel of interest and the rank of the median. The second estimation is a comparison of the brightness values in the pixel of interest and in the pixel closest to the pixel of interest in variational series. It must be said that each of these estimations, if used separately, often misidentify pixels as impulses. They allow for the detection of extreme values of brightness in different ways and in combination they complement each other. Since impulsive noise can change the brightness value of a pixel dramatically, an impulse can be identified by the height of its brightness jump in comparison with the surrounding pixels. Thus impulse detection can be reduced to the analysis of local image statistics within a window whose size is defined by a filter. It is well known that the difference between the rank of an impulse and the rank of the median in a local window is usually large [1]. In [3], Zhou Wang proposes the restoration algorithm. This algorithm composed of two parts impulse detection and noise cancellation. Many previously published algorithms such as those in [3] and [4] used an impulse detector to determine whether a pixel should be modified. A difference in our algorithm is that the detection results are also used to help the process of the second part noise cancellation.

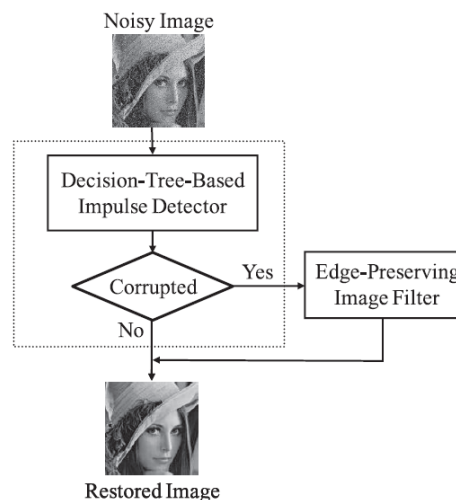
2.2 Efficient Impulse Detector

In [7] Chih-Yuan Lien proposes a new efficient impulse noise detector. The noise considered in this letter is fixed-valued impulse noise, also called salt-and-pepper noise, with uniform distribution. The algorithm is composed of two components: efficient impulse detector and edge preserving filter. The former determines which pixels are corrupted by fixed-valued impulse noise. The latter reconstructs the noisy pixels by observing the spatial correlation and preserving the edges efficiently. Let $p_{i,j}$ denote the current pixel at coordinate i,j and $(y_{i,j})$ denote its pixel value. For each pixel in an image, we define a 3×3 window centered on it first. Let represent the set of pixels within a 3×3 window centered on $p_{i,j}$. over four directions, only four of them are chose according to the variation in angle. The noise considered in this paper is random-valued impulse noise with uniform distribution. Here, we adopt a 3×3 mask for image denoising. Assume the pixel to be denoised is located at coordinate (i, j) and denoted as $p_{i,j}$, and its luminance value is named as $f_{i,j}$, as shown in Fig. 1. According to the input sequence of image denoising process, we can divide other eight pixel values into two sets: $W_{TopHalf}$ and $W_{BottomHalf}$. They are given as

$$W_{TopHalf} = (a, b, c, d)$$

$$W_{BottomHalf} = (e, f, g, h)$$

DTBDM consists of two components: decision-tree-based impulse detector and edge-preserving image filter. The detector determines whether $p_{i,j}$ is a noisy pixel by using the decision tree and the correlation between pixel $p_{i,j}$ and its neighboring pixels. If the result is positive, edge preserving image filter based on direction-oriented filter generates the reconstructed value. Other-wise, the value will be kept unchanged. The figure below shows the working of DTBDM.



2.1 Decision Tree based Impulse Detector

In order to determine whether $p_{i;j}$ is a noisy pixel, the correlations between $p_{i;j}$ and its neighboring pixels. Surveying these methods, we can simply classify them into several ways observing the degree of isolation at current pixel and determining whether the current pixel is on a fringe or comparing the similarity between current pixel and its neighboring pixels. Therefore, in our decision tree-based impulse detector, we design three modules isolation module (IM), fringe module (FM), and similarity module (SM). Three concatenating decisions of these modules build a decision tree. The decision tree is a binary tree and can determine the status of $p_{i;j}$ by using the different equations in different modules. First, we use isolation module to decide whether the pixel value is in a smooth region. If the result is negative, we conclude that the current pixel belongs to noisy free. Otherwise, if the result is positive, it means that the current pixel might be a noisy pixel or just situated on an edge. The fringe module is used to confirm the result. If the current pixel is situated on an edge, the result of fringe module will be negative (noisy free); otherwise, the result will be positive. If isolation module and fringe module cannot determine whether current pixel belongs to noisy free, the similarity module is used to decide the result. It compares the similarity between current pixel and its neighboring pixels. If the result is positive, $p_{i;j}$ is a noisy pixel; otherwise, it is noise free

2.4 Isolation Module

The pixel values in a smooth region should be close or locally slightly varying. The differences between its neighboring pixel values are small. If there are noisy values, edges, or blocks in this region, the distribution of the values is different. Therefore, we determine whether current pixel is an isolation point by observing the smoothness of its surrounding pixels. The pixels with shadow suffering from noise have low similarity with the neighboring pixels and the so-called isolation point. The difference between it and its neighboring pixel value is large. According to the above concepts, we first detect the maximum and minimum luminance values in $W_{TopHalf}$, named as $TopHalf_{max}$, $TopHalf_{min}$, and calculate the difference between them, named as $TopHalf_{diff}$. For $W_{BottomHalf}$, we apply the same idea to obtain $BottomHalf_{diff}$. The two difference values are compared with a threshold Th_{Ma} to decide whether the surrounding region belongs to a smooth area.

$$TopHalf_{diff} = TopHalf_{max} - TopHalf_{min}$$

$$BottomHalf_{diff} = BottomHalf_{max} - BottomHalf_{min}$$

DecisionI = true if ($TopHalf_{diff} \geq Th_{Ma}$) or ($BottomHalf_{diff} \geq Th_{Ma}$) false; otherwise.

Next, we take $p_{i;j}$ into consideration. Two values must be calculated first. One is the difference between $f_{i;j}$ and $TopHalf_{max}$; the other is the difference between $f_{i;j}$ and $TopHalf_{min}$. After the subtraction, a threshold Th_{IMb} is used to compare these two differences. The same method as in the case of $W_{BottomHalf}$ is applied. The equations are as

$IM_{TopHalf} = true if (f_{i;j} - TopHalf_{max} \geq Th_{IMb}) or (f_{i;j} - TopHalf_{min} \geq Th_{IMb}) false; otherwise.$

$IM_{BottomHalf} = true if (f_{i;j} - BottomHalf_{max} \geq Th_{IMb}) or (f_{i;j} - BottomHalf_{min} \geq Th_{IMb}) false; otherwise.$

2.5 Fringe Module

If $p_{i;j}$ has a great difference with neighboring pixels, it might be a noisy pixel or just situated on an edge, as shown in Fig. 6. How to conclude that a pixel is noisy or situated on an edge is difficult. We take direction E1 for example. By calculating the absolute difference between $f_{i;j}$ and the other two pixel values along the same direction, respectively, we can determine whether there is an edge or not.

2.6 Similarity Module

The last module is similarity module. The luminance values in mask W located in a noisy-free area might be close. The median is always located in the center of the variational series, while the impulse is usually located near one of its ends. Hence, if there are extreme big or small values, that implies the possibility of noisy signals. According to this concept, we sort nine values in ascending order and obtain the fourth, fifth, and sixth

values which are close to the median in mask W. The fourth, fifth, and sixth values are represented as $4^{th}inW_{i;j}$, $MedianInW_{i;j}$, and $6^{th}inW_{i;j}$. We define $Max_{i;j}$ and $Min_{i;j}$ as

$$\left. \begin{aligned} Max_{i;j} &= 6^{th}inW_{i;j} + ThSMa \\ Min_{i;j} &= 4^{th}inW_{i;j} - ThSMa \end{aligned} \right\} Equ(1)$$

III. NOISE REMOVAL TECHNIQUES

3.1 Edge -Preserving Image Filter

To locate the edge existing in the current W, a simple edge preserving technique is adopted. Here, we consider eight directional differences, from D1 to D8, to reconstruct the noisy pixel value. Only those composed of noise-free pixels are taken into account to avoid possible misdetection. Directions passing through the suspected pixels are discarded to reduce misdetection. Therefore, we use $Max_{i;j}$ and $Min_{i;j}$, defined in similarity module, to determine whether the values of d; e; f; g, and h are likely corrupted, respectively. If the pixel is likely being corrupted by noise, we don't consider the direction including the suspected pixel. In the second block, if d; e; f; g, and h are all suspected to be noisy pixels, and no edge can be processed, so $fi;j$ (the estimated value of pi) is equal to the weighted average of luminance values of three previously denoised pixels and calculated as $(a+b+c)/4$. In other conditions, the edge filter calculates the directional differences of the chosen directions and locates the smallest one (D_{min}) among them in the third block. The equations are as follows:

$$\left. \begin{aligned} fi;j &= (a + d + e + h)/4; \text{ if } D_{min} = D1 \\ fi;j &= (a + b + g + h)/4; \text{ if } D_{min} = D2 \\ fi;j &= (b + g)/2; \text{ if } D_{min} = D3 \\ fi;j &= (b + c + f + g)/4; \text{ if } D_{min} = D4 \\ fi;j &= (c + d + e + f)/4; \text{ if } D_{min} = D5 \\ fi;j &= (d + e)/2; \text{ if } D_{min} = D6 \\ fi;j &= (a + h)/2; \text{ if } D_{min} = D7 \\ fi;j &= (c + f)/2; \text{ if } D_{min} = D8 \end{aligned} \right\} equ(2)$$

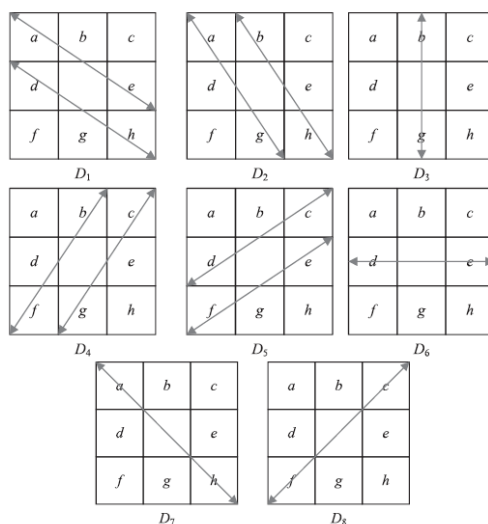


Fig. 3.1 Eight directional differences of DTBDM.

3.2 Impulse arbiter

In [1], the value of a pixel corrupted by the fixed-value impulse noise will jump to be the minimum/maximum value in gray scale, we can conclude that if $p_{i,j}$ is corrupted, $f_{i,j}$ is equal to MIN_{inW} or MAX_{inW} . However, the converse is not true. If $f_{i,j}$ is equal to MIN_{inW} or MAX_{inW} $p_{i,j}$ maybe corrupted or just in the region with the highest or lowest luminance. In other words, a pixel whose value is MIN_{inW} or MAX_{inW} might be identified as a noisy pixel even if it is not corrupted. To overcome this drawback, we add another condition to reduce the possibility of misdetection. If $p_{i,j}$ is a noise-free pixel and the current mask has high spatial correlation, $f_{i,j}$ should be close to $f_{i,j}$ and $f_{i,j}$ is small. That is to say, might be a noise-free pixel but the pixel value MIN_{inW} is or MAX_{inW} if $f_{i,j}$ is small. We measure $f_{i,j}$ and compare it with a threshold to determine whether $p_{i,j}$ is corrupted or not. The threshold, denoted as T_s , is a predefined value. Obviously, the threshold affects the performance of the proposed method. A more appropriate threshold can achieve a better detection result. However, it is not easy to derive an optimal threshold through analytic formulation. According to our experimental results, we set the threshold T_s as 20. If $p_{i,j}$ is judged as a corrupted pixel, the reconstructed luminance value $\hat{f}_{i,j}$ is equal to $f_{i,j}$; otherwise, $\hat{f}_{i,j} = f_{i,j}$.

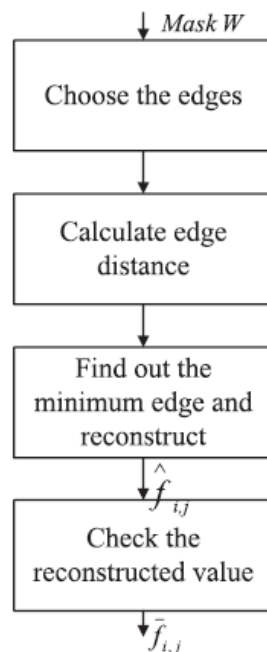


Fig. 3.2 Dataflow of edge-preserving image filter.

3.3 Noise cancellation

In [30], the noise cancellation scheme is only applied to those pixels considered as impulses ($f_{i,j} = 1$). For an impulse pixel at position (i,j) two $(2N_c + 1) \times (2N_c + 1)$ sized windows are employed: The first window is the local window centered about the impulse pixel and the second window is a remote window located at a different place in the image with its center at position (k, l) . Since the whole image may contain a large number of complete $(2N_c + 1) \times (2N_c + 1)$ windows, the remote window should be selected from one of them.

IV. CONCLUSION

The proposed method for efficient removal of random-valued impulse noise is proposed in this paper. The approach uses the decision-tree-based detector to detect the noisy pixel and employs an effective design to locate the edge. With adaptive skill, the quality of the reconstructed images is notably improved. In this work, I have presented a new noise level estimation algorithm. The comparison with the several best state of the art methods shows that the accuracy of the proposed approach is the highest in most cases. Among the methods with similar accuracy, proposed algorithm is always more than 15 times faster. Since the proposed method does not require the existence of homogeneous areas in the input image, it can also be applied to textures.

During denoising experiments, I observed that a higher noise level estimation accuracy leads to a higher denoising quality in most cases. It shows the importance of a careful selection of the noise estimator in a denoising application. It is also observed that the denoising quality of proposed algorithm was approximately the same as that with the true noise level if the image was not a stochastic texture; hence the proposed method can be successfully applied in image denoising. This approach can also be utilized in image compression and segmentation applications which require noise level estimation..Extensive experimental results demonstrate that the performance of proposed technique is better than the previous lower complexity methods and is comparable to the higher complexity methods in terms of both quantitative evaluation and visual quality. It requires only low computational complexity and two line memory buffers. Therefore, it is very suitable to be applied to many real-time applications.

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